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Demand Response with Model Predictive Comfort Compliance in an Office Building

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Abstract—The change in the electricity supply towards solar and wind is creating new stability and balancing challenges for the electricity grid. A solution to these challenges is to change the consumption of the demand-side in particular buildings. Efforts to help change the demand-side in buildings evolves around the idea of Demand-Response. However, the impact of moving, shedding or filling loads in buildings has a large impact on building occupants. In order to further the spread of DR systems, it is necessary to consider the impact of DR on comfort. In particular to assess it to ensure compliance with both soft demands for comfort, as well as harder demands such as minimum running systems and law requirements. Furthermore, the impact on comfort needs to be calculated to an order of accuracy that is high enough to ensure proper scheduling of DR events while also meeting acceptable thresholds for the effects on the occupants. In this paper we evaluate to which degree a Model Predictive Control (MPC) system can deliver comfort compliance. We will discuss the design of a DR capable MPC system that can plan ahead and use a building's potential for DR while also providing comfort for occupants. We also present the results from a case-study utilizing MPC in an office building. We study the compliance over multiple times a day and week to consider different building states and occupancy patterns, taking into account external factors such as weather patterns and building structures. Lessons learned are summarized to inform the design of such systems and characterize their applicability. We also study the value of occupancy predictions and how these affect predictions compared to utilizing standard schedules for a building.

I. INTRODUCTION

Today's world of electrical supply is changing due to the introduction of renewables. It is changing from a static model, where the provider has full control, to one that is more fluid and dependent on external factors, such as, sun and wind patterns. This change introduces new challenges for the providers, as their production is harder to control. A potential solution to these challenges is that consumers change their consumption to follow the new patterns of supply. Thus, Demand-Response was conceived and begun implemented in larger areas. However, as of now, DR focuses on large operations and often calls for an all-or-nothing event [1]. Such an event can be asking a business to cut usage for four days a year or an office building to turn off the HVAC for an hour during peak hours in order to reduce the load on the grid [2]. However, shutting down interrupts production, and shutting off the HVAC in peak periods could mean a lowering of the air quality or too high temperatures for workers to be comfortable. Thus, we introduce the term *Comfort Compliance*, a second parameter to ensure the users of a building are taken into

consideration when a DR event is scheduled and effectuated in a building, be it a school, an office or a business building.

Comfort compliance covers requirements for occupants that fall into two categories: soft and hard. Soft comfort requirements are requirements which make the surroundings for a given occupant comfortable and optimal. These include keeping the temperature optimal, CO₂ levels low and lighting at a high level to avoid eye-strain. Hard comfort requirements cover law requirements, work-space requirements and health requirements. These can include healthy temperature ranges, a ceiling on CO₂ and a minimum of lighting levels for workers to work safely. Comfort compliance as a term covers all these and should as far as possible be quantified as a number of factors for how comfortable a given situation is for the inhabitants of a building. Satisfying comfort compliance allows us to ensure that adherence to a DR signal does not jeopardize the health and safety of occupants. This also gives us a measure for evaluating a given scenario and compare it to others, putting the occupants in the forefront rather than the bottom line.

Existing work on integration of commercial buildings in DR programs has considered automated demand response based on static preprogrammed building control [3]. However, the impact on comfort was only considered in manual pre- and post-deployment audits. So far occupancy comfort has primarily been considered for energy efficiency and not DR [4]. Therefore, we have identified several shortcomings in existing work: a) occupant comfort has only been addressed to a limited extent [5], e.g., ensuring control will satisfy national building and work regulations and in constrained occupancy settings [6], [7], b) the impact of predictable occupant behavior has not been included in building control for DR [5] and c) many proposed solutions do not provide the requested load change [3]. In our previous work we proposed a system designed as a Model-Predictive Control (MPC) system named ADRALOC [1]. The advantage of MPC systems is the ability to plan ahead and thereby enable proactive actions. The ADRALOC system uses modeling to not only assess the DR capacity, but also to assess the impact on occupant comfort. The paper presented initial results for implemented subcomponents of ADRALOC.

In this paper, we present an extensive end-to-end evaluation focusing on the ability of the system to provide comfort compliance. In the following, we will start out by discussing the challenges that are caused by including occupant comfort in the equation. We then present our system configuration

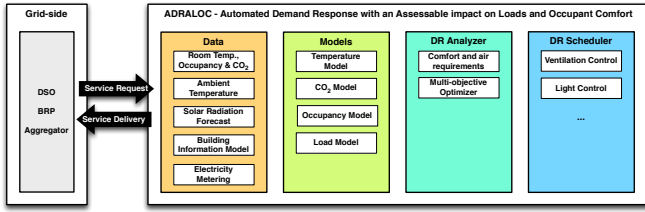


Fig. 1: System Setting for the ADRALOC system including system components and data sources.

briefly and follow with a description of our current testbed. Results from the testbed will then be presented and analyzed before we discuss the lessons learned. Finally, we consider the issue of sensing occupancy and how it affects the complete system.

II. COMFORT COMPLIANCE CHALLENGES

A traditional Building Management System (BMS) relies on distributed controllers to run control loops. These, typically, take a setpoint and a stream of sensor values (of same modality) as input and based on this produce a control signal. The control signal is this continuously adapting to prevailing conditions. Often a deadband is configured that allows the controlled modality to drift which can simplify the control signal. The result is that system aims to instantly correct problems once they occur without considering building use, previous or future. In stark contrast are MPC systems, where models a head of time help proactively ensure that certain parameters are maintained as well as decide which parameters take precedence. The ADRALOC system uses models to predict everything from occupancy to building reactions to various settings in order to predict events and change settings to prepare for these to optimize building operations.

The main issue for a MPC is which parameters to take into account, as well as decide what are the setpoints. For various scenarios, the same setpoints can have drastically different values as the type of use a building sees varies. For example, according to the Danish 2015 building regulations [8], comfort settings for a factory worker with a large amount of manual labor can be between 16 and 20 degrees, while a sedentary office worker will require between 20 and 23 degrees. In some situations, lighting levels needs to be higher, laboratories for example, while it is acceptable for it to be lower in an office area where screens do much of the work.

III. THE ADRALOC SYSTEM

ADRALOC is a system proposed by Kjærgaard et al. [1] with two main goals: to enable buildings to be energy flexible as well as to deliver comfort compliance. The ADRALOC system aims to achieve these goals using prediction algorithms for multiple parameters for performing Model Predictive Control on buildings.

The ADRALOC system consists of a number of components as illustrated in Figure 1. A data aggregation component with a time-series database and a metadata database are required for accessing the necessary data to populate models and

drive prediction software. For the DR analyzer / scheduler we use the Controleum Framework [2], a multi-objective optimization framework using genetic algorithms. Zone-based indoor climate models are developed in Modelica, electricity forecasting models [9] in Java and wrapped in FMU wrappers, and occupancy prediction is done by the OccuRE system [10]. External data is accessed via drivers developed in Python and stored in sMAP [11] which offers fast querying over a time-series database.

Under normal operation, the DR analyzer will constantly retrieve sensor-information from sensors and forecast information. Based on these data, the analyzer will create plans for building control and assess these via building models using the occupancy predictions from OccuRE. The scheduler creates plans that adhere to various suggested DR events and evaluates the feasibility of these before creating a final schedule. The resulting schedule is passed to the scheduler of the building in question. The scheduler then enacts the schedules while the analyzer waits for a new configuration or an allotted wait-time before it begins anew. This ensures a steady stream of schedules utilizing the latest sensor information and forecasts which helps alleviate issues with unforecasted events and inaccurate models. Streaming schedules also means that the scheduler has schedules for a longer time-frame, allowing for network breakdowns or crashes in other parts of the system.

In the case of a DR event, the setup changes. The DR events supported by ADRALOC consist of power cut requests which could be handled by moving or shedding loads in a building. A service request for the DR event is sent by the grid-side via an OpenADR message, e.g., from a Distribution System Operator (DSO), Balance Responsible Party (BRP) or an aggregator. Once a request is received, the DR analyzer evaluates the service request by attempting to live up to the restrictions. If this is possible, it reports back with how much energy it estimated it would have spent as well as how much energy a new plan will use along with the schedule that adheres to the event(s). If not, it will instead respond with how much energy it will use if it attempts to reduce energy use to a minimum given the current comfort requirements as well as law requirements. The requesting entity is then responsible for determining if the responses from different buildings can be combined in order to allow it to live up to a DR signal or not. If not, it can request a second round of negotiations slashing comfort requirements to only allow for legal requirements, not specific occupant comfort. Once all replies have been gathered, the requesting grid-side entity is then responsible for choosing the schedules that live up to the DR event, if possible, and send these to the scheduler. It will also notify the DR analyzer of the new settings and tell it to adhere to these for the set duration. Please consult [1] for further details on the system.

IV. TEST SETUP

For evaluating comfort compliance of the ADRALOC system we have applied two types of testing: verification of the system architecture through historical data and verification

through live testing. All results are for an 3000 m² office building at the GreenTech Center (GTC) in Vejle, Denmark named the GTC House. The live setup consists of an ADRALOC instance configured for scheduling DR events for the GTC House. In this particular test setting we are only able to control the HVAC due to building control restrictions. For historical data we run the optimization and evaluation algorithms on data available from a historian collecting data from all sensors and actuation points in the office building for more than a year.

The historical evaluation enables us to consider many different scenarios as we have access to large amounts of historical data for the building being used, allowing us also to model longer DR events. For the historical testing the system is configured to only utilizing historical data rather than current data. This goes for both sensor information and stored weather forecasts. We then run OCCURE utilizing the historical data in order to create historical occupancy predictions. With this as the data foundation, we can then run the prediction algorithm for the GTC House, allowing for complete shutoff of the HVAC system in one-hour intervals. One hour was chosen, as this is a relevant DR event time resolution but the system it is current form supports time resolutions down to minutes if relevant. The algorithm first creates a prediction using the ANN neural network [9] for the power consumption of the building based on the the data for a given period. It then proceeds to model out a series of DR events, each of various lengths, in order to see the ramifications of such an event and show whether the algorithm will allow a legal event and disallow the rest. It yields two results for each: a comfort result and a legal result. The comfort result will tell if an event is acceptable within comfort parameters, while a legal result will allow an event even if it begins to affect occupant comfort, but not if legal requirements are not satisfied.

V. RESULTS

The live version of the ADRALOC system has been used to make eight live tests. The tests have been conducted at different times a year (February to April) and different times of the day between 10-15. In all cases the ADRALOC system predicted that comfort compliance could be sustained. The impact on the power consumption of the ventilation in all cases is shown in Figure 2. From the figure one can observe that in all cases the consumption drops to around 1 kW highlighted by the dotted line. The drop depends on the time of day and year as the ventilation system has different loads. The February events in the lower end around 4-6 kW and the April events in the higher end up to 10 kW. If we consider the rebound effect after each DR event is finished it is high and short for the February events and low and long for the April events. The difference in the rebound effect can be attributed to the available additional capacity in the ventilation under different base loads. In each of the figures as reference we also include the ventilation consumption on nearby days with no control as reference. The consumption of all loads in the GTH House is on average around 25 kWh. Therefore, depending on the time

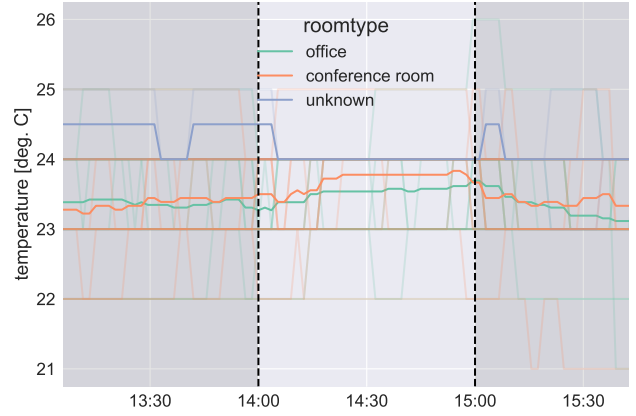
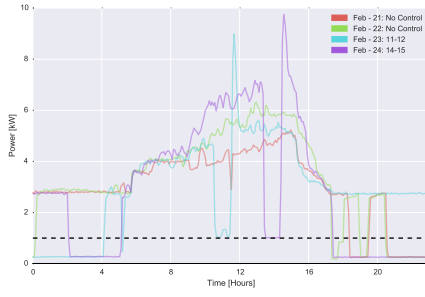


Fig. 4: February 23nd 2017 - Temperature levels in rooms

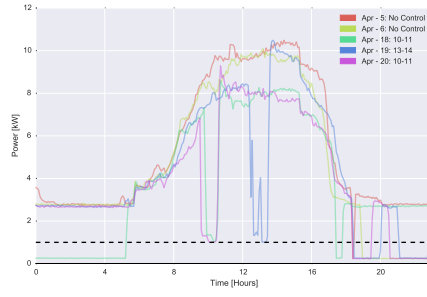
of year the above results demonstrate an ability to cut from 16% to 40% of the building's total consumption.

To study the effect of DR events on comfort compliance we consider CO₂ and temperature measurements in the building before, during and after DR events. Figure 3 shows curves of CO₂ under three of the eight DR events for different rooms. Comparing the curves we can observe that in most cases for both office and conference rooms the CO₂ levels increase with 100-200 ppm. This increase also keep the level below soft levels as predicted by our models. Only a few heavily occupied rooms deviate from this pattern and has a much larger increase to 1200-1500 ppm. This is most probably due to unexpected use of the room, likely with more occupants than predicted or maybe even intended for the room. The data for the five other DR events not displayed shows the same trends. Figure 4 shows temperature measurements for one of the DR events where we can observe a very small change in temperature. The temperature curves for the seven other DR events not displayed shows the same trends. It is here relevant to note as the building like most other Danish buildings is heated mainly via radiators using district heating. Therefore, only overheating could have been a potential issue as the radiators will keep rooms heated during an event. However, no instances of overheating is observed but as the events took place with outdoor temperature below 15°Celsius this could be a more pressing issues with higher summer temperatures.

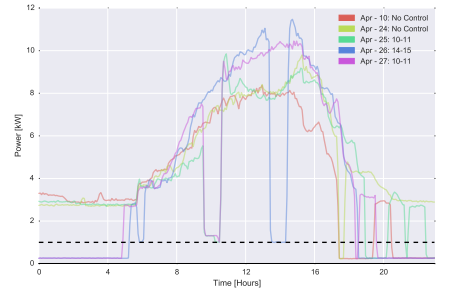
In the live tests we consider one-hour DR events. Running experiments on historical data allow us to visualize the predicted effects of any DR event. This allows for an overall graph for a day with expected power consumption and potential DR events as shown in Figure ?? to 6. In the paper we present the results for two winter and one summer day to consider different weather situations. The blue arch on the figures displays the predicted consumption of the building for the day as estimated at midnight. The bars in the same color display the length of each proposed DR event before conditions exceed the building's comfort requirements. Each of the periods does not exceed 5 hours within working hours although the actual request is 10 hour events. However, note



(a) End of February

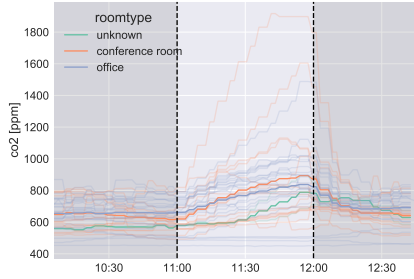


(b) Middle of April

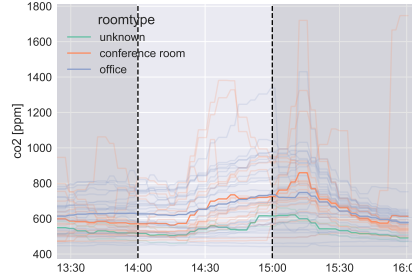


(c) End of April

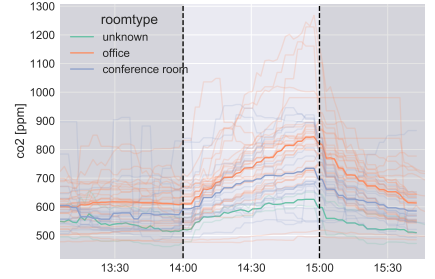
Fig. 2: Ventilation system power consumption during days with DR events and days with no control.



(a) February 22nd 2017



(b) February 23rd 2017



(c) April 26 2017

Fig. 3: CO₂ levels in rooms during DR events.

that after working hours, events can occur again or, in the case of events starting at 14 or 16 in the afternoon, continue uninterrupted for the full duration. This is because without occupants in the rooms, CO₂ will not continue to rise but rather plateau and diffuse naturally. In all cases where the DR event is not allowed to the requested 10 hour period, it is due to temperatures becoming unstable (too high) or CO₂ conditions exceeding acceptable thresholds. These events assume normal running conditions of the building. As additional error sources can impact temperature and CO₂ levels that we do not have sensor data on, the models are not overly precise. Such events include radiators turning on and off, including setpoints being changed manually by occupants, as well as occupants opening door and windows, all of which will change room temperature and CO₂ conditions from the modeled numbers.

VI. LESSONS LEARNED

In this section we summarize three lessons learned.

A. Sensor Problems

Sensor problems is an issue when deploying MPC systems such as ADALOC in real-world buildings. In the above experiments, we had to exclude rooms due to insufficient sensor-data for one or more pertinent sensors. We have also been unable to model on all months, as faulty sensors have stopped reporting with an adequate frequency in certain periods or suddenly begun reporting values out of reasonable

Each set of bars represents the forecasted feasible DR event beginning at X O'clock, e.g., DR10 at 10 O'clock.

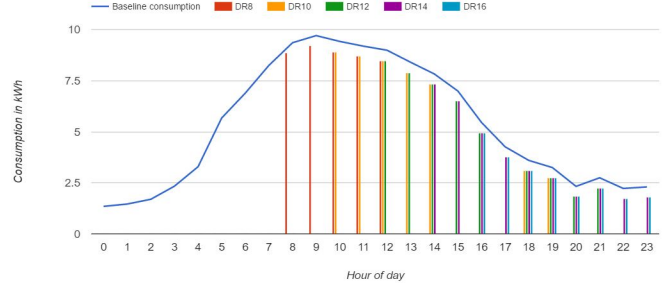


Fig. 5: Winter (December 7th 2016)

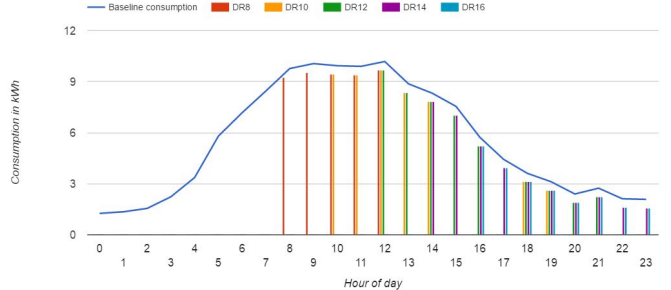


Fig. 6: Summer (July 27th 2016)

ranges, requiring their exclusion. Every room in GTC House contains sensors for occupancy presence, temperature and CO₂. A subset of these rooms has one of the modalities covered by multiple sensors and many rooms have data quality

issues. In order to handle this, the system will take a random sensor if more than one are present, but this is not necessarily optimal, as a sensor at the ceiling in a 2-story room will produce different readings from one close to a desk in an office environment. As for missing sensors, the program currently discards rooms without enough viable sensor information. This, however, is not optimal, as in some cases, it means that less than half the actual rooms are evaluated. If these are rooms with high occupancy, the predictions suddenly ignore issues with CO₂ levels and temperature in these rooms.

B. Lack of High Granularity Sensing

Not all sensors are optimal for the intended control. For example, with PIR sensors as the only occupancy sensing sensors available, models will use historical data to predict the number and impact of occupants. This, in turn, means that as rooms change number of inhabitants, the zone model parameters fail to properly account for the change in occupancy. Even worse is if an office changes use, for example changes from meeting room to office or vice-versa. Also, the windows and doors are not equipped with sensors for detecting state. This is an error source for the model-based predictions and is something that is incredibly hard to take account for in MPC scenarios. For future work and better control, these types of issues need to be considered and either taken into account by models or rectified with retro-fitting of pertinent sensors. Or, in the case of windows, these can be locked to prevent user interference.

C. Occupancy Importance

Another important factor is occupancy and the accuracy of occupancy predictions. To evaluate the impact we have compared our model results to the actual building data and a simulated situations with and without occupancy. Figure 7 and 8 show the simulations if the building were either full or empty throughout the 24-hour period of December 7th, 2016. When simulating DR events without occupancy in the building the system accepts and schedules all service requests for DR events. This is due to that there is no occupants to impact the CO₂ and temperature levels, resulting in the building being capable of scheduling any sort of event. For the simulation scenario where the building is in full use through out the day, we see the same pattern as in the historical modeling. The pattern begins early in the day with 5 hour periods of DR potential before comfort limits are reached. As mentioned earlier, some meeting rooms were entirely excluded from consideration during these tests due to the model parameters being very odd for the room sizes due to faulty sensor data. For instance, the room's model results for CO₂ skyrocketing from 424 to 4999 within an hour and to 9284 in three hours. In this case related to a parameter for the occupancy modeling underpinning how occupancy does matter quite a bit for the modeling. This is also a consideration for future work, as our current model simply approximate a multiplier of occupancy with a PIR reading. This might work for offices with a fairly fixed number of inhabitants, but for other rooms, such as meeting rooms or cafeterias etc, it can be extremely

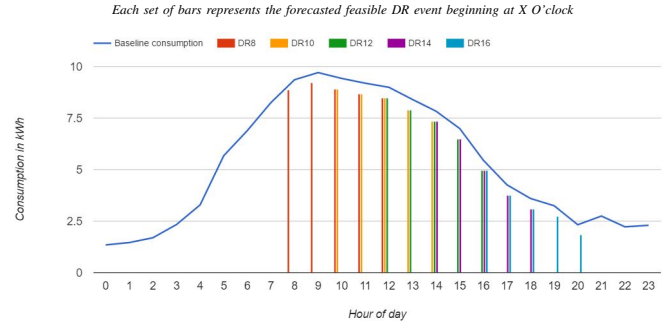


Fig. 7: December 7th 2016, simulated full building all day

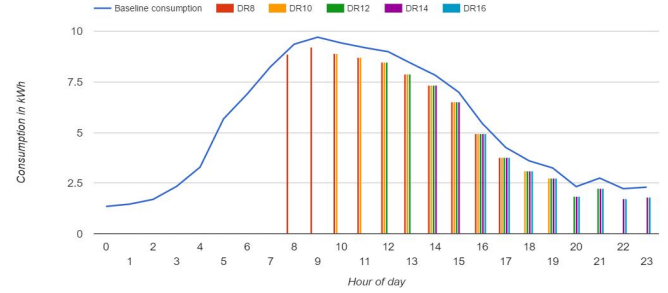


Fig. 8: December 7th 2016, simulated empty building all day

problematic using a static multiplier. Furthermore, as some rooms have windows that are all without sensors that users are known to open on a frequent basis, it becomes clear that we are missing certain data in order for the parameter estimation of our models to be highly accurate.

In general, it seems that the time of day does not particularly affect the possible length of DR events. However, in our results early events are rejected to be scheduled due to CO₂ concerns and latter due to temperatures. The timing of temperature rejections could be linked both the heat generation from occupants and the equipment they use and outside temperatures and sunshine on the building. Showing the importance of taking into account occupancy and external data.

VII. DISCUSSION

ADRALOC shows promise in regards to controlling a building for DR events using models to predict the future comfort of occupants. The most interesting results are that the models maintain a fairly good estimation of short-term predictions while the multiple-hour predictions begin to falter. On the other hand, if incorporating the ADRALOC system tighter to the building control than on/off schedules would enable precooling and prevention. This would result in that the long-horizon calculations would be less important for occupant comfort.

The main issue currently seem to be the issue of estimating the inhabitants of a room with only PIR sensors causing the models to attempt to estimate what number of people triggered the PIR reading. Therefore, the system could benefit from more inputs related to the actual number of occupants to calculate more precisely the impact of occupants. Furthermore, the building issues that we do not have control over, mainly door and windows being opened, and radiators with manual

setpoints, cause the parameter estimations to be further off. Because of this we need to reevaluate the parameter estimation approach. Is this approach only applicable to building under complete control, or can it still be beneficial if we account for and model around all manual settings affecting the room? Or should parameter estimations be done supervised or otherwise use data cleaning methods to minimize or eliminate these inaccurate readings? Our suggestion would be to use additional tools to set up sensors during a supervised period for parameter estimation data collection or have inhabitants manually report on these events so the data may be added to the total data-pool before parameter estimation is performed. New technology boasts simple clip-on radiator meters that can also be used for such a scenario to monitor this parameter as well.

This, however, does not lead to the actual ADALOC model to be deemed unusable. Rather, it puts into perspective the daunting task of MPC in buildings. Even with large amounts of data, it is still a variable process of creating the correct models and the building control systems also need to provide the needed access in order to do more than simply turn them on and off for DR events. If we wish to optimize the building, we need a bare minimum of setpoint control. Finally, this entire process underlines the need for the coverage of sensors and their accuracy, what to sense and how to handle a lack of monitoring capability or actuation points as well as solid data validation tools for historical data to ensure the data is consistent and lives up to the requirements of the algorithms in the control system.

VIII. CONCLUSION

In this paper we have provided results of implementing building control in an office building with the intent to perform DR events on a building with a restricted control potential, i.e. only on/off settings for the HVAC system. Furthermore, we have shown the potential for longer duration events and the capability of prediction algorithms using historical data to predict impacts on building comfort. The control is based on models taken into account comfort concerns, such as CO₂ limits and temperature ranges that fall within comfort requirements for the season and building use.

We have identified a number of problems that arise using the proposed system by looking at the data predictions, including parameter estimation, the low accuracy of occupancy prediction due to PIR sensors being the only registration method. This also opens up to other building issues such as faulty sensors, faulty updates in the time-series database and buildings with additional aspects that have no sensors, such as doors, windows and radiators.

Finally, we have concluded that the system has potential, but that certain problems with buildings can cause parameter estimation to be so faulty, that long-period predictions are not safe enough to use for these buildings. This leads us to having to re-evaluate how we estimate parameters, minimum requirements for safe parameter estimation in the data. It also gives rise to concerns for long-term predictions with comfort compliance in mind, as such a system needs to be more precise

than the initial version of the system has shown to be, in order to ensure that in particular CO₂ levels remains below limits.

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REFERENCES

- [1] M. B. Kjærgaard, K. Arendt, A. Clausen, A. Johansen, M. Jradi, B. N. Jørgensen, P. Nellen, F. C. Sangogboye, C. Veje, and M. G. Wollsen, "Demand response in commercial buildings with an assessable impact on occupant comfort," in *Proceedings of the IEEE International Conference on Smart Grid Communications*, 2016.
- [2] S. N. Ghoreishi, J. C. Sørensen, and B. N. Jørgensen, "Enhancing state-of-the-art multi-objective optimization algorithms by applying domain specific operators," in *Proceedings of the IEEE Symposium Series on Computational Intelligence*, 2015, pp. 877–884.
- [3] M. A. Piette, S. Kiliccote, and G. Ghatikar, "Field experience with and potential for multi-time scale grid transactions from responsive commercial buildings," in *ACEEE Summer Study on Energy Efficiency in Buildings*, 2014.
- [4] S. Chen, T. Liu, Y. Zhou, C. Shen, F. Gao, Y. Che, and Z. Xu, "She: Smart home energy management system based on social and motion behavior cognition," in *Proceedings of the 2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, 2015, pp. 859–864.
- [5] M. Behl and R. Mangharam, "Sometimes, money does grow on trees: Data-driven demand response with dr-advisor," in *Proceedings of the 2Nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments*, ser. BuildSys '15, 2015.
- [6] E. Vrettos, E. C. Kara, J. MacDonald, G. Andersson, and D. S. Callaway, "Experimental demonstration of frequency regulation by commercial buildings; part ii: Results and performance evaluation," *IEEE Transactions on Smart Grid*, 2017.
- [7] G. Costanzo, S. Iacovella, F. Ruelens, T. Leurs, and B. Claessens, "Experimental analysis of data-driven control for a building heating system," *Sustainable Energy, Grids and Networks*, vol. 6, pp. 81 – 90, 2016.
- [8] "Danish building regulations 2015," <http://byggningsreglementet.dk/english/0/40>, accessed: 2017-04-13.
- [9] M. G. Wollsen, M. B. Kjærgaard, and B. N. Jørgensen, "Influential factors for accurate load prediction in a demand response context," 2017.
- [10] M. B. Kjærgaard, A. Johansen, F. Sangogboye, and E. Holmegaard, "Occure: An occupancy reasoning platform for occupancy-driven applications," in *Proceedings of the 19th International ACM SIGSOFT Symposium on Component-Based Software Engineering (CBSE)*, 2016, pp. 39–48.
- [11] S. Dawson-Haggerty, X. Jiang, G. Tolle, J. Ortiz, and D. Culler, "smapi: A simple measurement and actuation profile for physical information," pp. 197–210, 2010.